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Interdisciplinarity and impact: Distinct effects of variety, balance and disparity

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Abstract

Interdisciplinary research is increasingly recognized as the solution to today's challenging scientific and societal problems, but the relationship between interdisciplinary research and scientific impact is still unclear. This paper studies the relationship between interdisciplinarity and citations at the paper level. Different from previous literature compositing various aspects of interdisciplinarity into a single indicator, this paper uses factor analysis to uncover distinct aspects of interdisciplinarity and investigates their independent dynamics with scientific impact. Three uncovered factors correspond to variety, balance and disparity respectively. Subsequently, we estimate Poisson models with journal fixed effects and robust standard errors to investigate the relationship between these three factor and citations. We find that long-term (13-year) citations (1) increase at an increasing rate with variety, (2) decrease with balance, and (3) increase at a decreasing rate with disparity. Furthermore, interdisciplinarity also affects the process of citation accumulation: (1) although variety and disparity have positive effects on long-term citations, they have negative effects on short-term (3-year) citations, and (2) although balance has a negative effect on long-term citations, its negative effect is insignificant in the short run. These findings have important implications for interdisciplinarity research and science policy.

Keywords: interdisciplinarity; impact; citation delay, variety; balance; disparity

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1. Introduction

Interdisciplinary research has been increasingly viewed as the remedy for the challenging contemporary scientific and societal problems. The National Academies (2004) defined that "Interdisciplinary research (IDR) is a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice." As important ideas often transcend the scope of a single discipline, interdisciplinary research is the key to accelerate scientific discoveries and solve societal problems.

Given the normative interest in and the policy push for interdisciplinary research, it's important to empirically investigate the consequences of interdisciplinary research. For example, Rafols, Leydesdorff, O'Hare, Nightingale, and Stirling (2012) showed that multidisciplinary institutions are disadvantaged in discipline-based evaluation systems, while Millar (2013) demonstrated a positive effect of interdisciplinary dissertation research on career placement and publication productivity of doctoral graduates. Bibliometric studies have also explored the relationship between interdisciplinary research and citation impact, but findings are mixed. For example, Steele and Stier (2000) found a positive effect of interdisciplinarity on citation impact for environmental sciences papers, where interdisciplinarity was measured as the disciplinary diversity of the cited references. Rinia, van Leeuwen, van Vuren, and van Raan (2001) studied physics programs in the Netherlands and operationalized interdisciplinarity as the ratio of non-physics publications. They found significantly negative correlations between interdisciplinarity and non-normalized citation-based metrics, but correlations became insignificant when field-normalization took place. Levitt and Thelwall (2008) found that interdisciplinary papers received fewer citations in life and physical sciences but not in social sciences, and interdisciplinary papers were defined as papers published in journals assigned to multiple subject categories. Larivière and Gingras (2010) analyzed all Web of Science (WoS) articles published in 2000, measured interdisciplinarity as the percentage of its cited references to other disciplines, and found an inverted *U*-shaped relationship between interdisciplinarity and citations.

One possible explanation for these conflicting results pertains to their different choices of the interdisciplinarity measure. On the one hand, a number of interdisciplinarity indicators have been proposed, at various levels (e.g., paper, journal, institution, and fields) and using various bilometric information (e.g., disciplinary memberships of authors, published journals, or cited references). On the other hand, the concept of interdisciplinarity remains an abstract and complex one (Wagner et al., 2011). One useful conceptualization is to view interdisciplinarity as the diversity of disciplines invoked in the research (Porter & Rafols, 2009; Stirling, 1998, 2007). Furthermore, diversity has three distinct components (Stirling, 2007, p. 709):

> *Variety is the number of categories into which system elements are apportioned. It is the answer to the question: 'how many types of thing do we have?'*
>
> *Balance is a function of the pattern of apportionment of elements across categories. It is the answer to the question: 'how much of each type of thing do we have?'*
>
> *Disparity refers to the manner and degree in which the elements may be distinguished. It is the answer to the question: 'how different from each other are the types of thing that we have?'*

Many studies have devoted to compositing all aspects of interdisciplinarity into one single indicator. However, this paper adopts an opposite approach: we decompose different aspects of interdisciplinarity and explore their unique relationships with citation impact, at the individual paper level. Given that interdisciplinarity is an abstract and multidimensional concept, there might not be a straightforward answer to the question of whether interdisciplinary research draws higher impact. Instead, we should ask the question in another way: what kinds of interdisciplinarity have positive/negative relationships with citation impact? In addition, nuanced understanding of the divergent dynamics underlying different aspects of interdisciplinarity is also important for informing interdisciplinary research and science policy.

In addition to the relationships between interdisciplinary and long-term citation impact, we are also interested in the association between interdisciplinarity and the process of citation accumulation. Previous literature has long explored the process of citation ageing and reception, which can be affected by a number of paper features and social factors (Garfield, 1980; Glänzel & Schoepflin, 1995; Wang, 2013). One intriguing topic is the phenomenon of delayed recognition or sleeping beauty, where a paper is uncited for a long time and then suddenly takes off and becomes highly cited (Braun, Glänzel, & Schubert, 2010; Burrell, 2005; Garfield, 1980; Glänzel, Schlemmer, & Thijs, 2003; Glänzel, Thijs, & Schlemmer, 2004; Van Raan, 2004). Scholars have also observed that citations to work in a different discipline have a longer delay than citations to work in the same discipline (Rinia, van Leeuwen, Bruins, van Vuren, & van Raan, 2002; Rinia, Van Leeuwen, Bruins, Van Vuren, & Van Raan, 2001), suggesting that interdisciplinary research papers might be more likely to encounter citation delays. Therefore, we directly investigate the relationship between interdisciplinarity and citation delay, contributing to the understanding of dynamic knowledge diffusion processes of interdisciplinary research and research evaluations on interdisciplinary work.

2. Data and methods

We analyzed all the journal articles published in 2001 indexed in the Thomson Reuters Web of Science (WoS). Only articles were analyzed, while all other document types such as reviews and letters were excluded. The year 2001 was chosen so that studied papers could have a sufficiently long period to accumulate their citations (Wang, 2013).

2.1. Interdisciplinarity measures

Following previous literature, we constructed interdisciplinarity measures for each individual articles based on the disciplinary profile of its cited references, since referencing to prior literature in various disciplines indicates drawing and integrating knowledge pieces from these disciplines. Specifically, we constructed interdisciplinarity measures based on the WoS subject categories (SCs) referenced by each article. Interdisciplinarity measures constructed in this paper are listed in Table 1, which have been commonly used in the literature (Leydesdorff & Rafols, 2011; Rafols et al., 2012; Stirling, 2007).

---------------- *INSERT TABLE 1 ABOUT HERE* ----------------

Ratio of references to subject categories different from the focal paper itself (ratio oth-disc refs) has been used since a long time to capture the activity of borrowing knowledge from other disciplines. The number of referenced subject categories indicates the richness or the variety of disciplines invoked in the focal paper. The Gini index captures the inequality, unevenness, or unbalance of the distribution of references across involved disciplines. Note that a larger Gini indicates a lower level of diversity, so we use 1 – Gini in our analysis, which would have the same direction as diversity/interdisciplinarity. In addition, Shannon entropy and Simpson index capture both variety and balance of referenced disciplines. Note that the original Simpson index is formulated as $\sum {p_i}^2$, which is also negatively associated with diversity. The formula adopted here, $1 - \sum {p_i}^2$, is positively associated with diversity, and also referred to as Simpson index or Gini-Simpson index in the literature. The average dissimilarity between referenced subject categories focuses on the disparity between invoked disciplines. At last, the Rao-Stirling diversity is a composite measure of all the three diversity components: variety, balance, and disparity.

Because the last two interdisciplinarity measures cannot be constructed if the focal article references fewer than two subject categories, we excluded these articles from the analysis. Nevertheless, regressions using the whole dataset for the other measures yielded consistent results. In total, our data have 646,669 papers.

2.2. Factor analysis

We used factor analysis to uncover components underlying these interdisciplinarity measures. The first step was to determine the number of factors to retain. A classic approach is Kaiser's eigenvalue greater than one rule (Kaiser, 1960). The idea is that the retained factor should explain more variance than the original standardized variables. Horn's parallel analysis modified Kaiser's rule, where the criterion for each eigenvalue is different and also superior to one, and these criteria are obtained from a Monte-Carlo simulation (Horn, 1965). Cattell's scree test provided a graphical strategy: plotting the eigenvalues against the component numbers and searching for the elbow point (Cattell, 1966). However it does not yield a definitive number of factors to retain, which still relies on subjective judgments of the researcher. Recently, Raiche, Walls, Magis, Riopel, and Blais (2013) developed numerical solutions for Cattell's scree test: (1) the optimal coordinate solution for the location of the scree and (2) the acceleration factor solution for the location of the elbow. We implemented all these methods to determine the number of factors.

After determining the number of factors to retain, we extracted these factors using the varimax rotated principal components method. Specifically, we used the *principal* function in the *R* package *psych*. In addition, the number of referenced subject categories is highly skewed, so its nature logarithm was used in the factor analysis.

2.3. Regression analysis

To study the relationship between interdisciplinarity and long-term citation impact at the article level, we ran regressions, using the number of long-term citations (in a 13-year time window from 2001 to the end of 2013) as the dependent variable and the interdisciplinarity measures and extracted factors as explanatory variables. To explore the association between interdisciplinarity and citation delay, we further estimated the effects of interdisciplinarity on short-term citation (in a 3-year time window from 2001 to 2002) and compared them with effects on long-term citations. In addition, we also adopted another dependent variable, *citation speed*, which measures how fast in general a paper accumulates its citations (Wang, 2013):

$$citation\ speed = \frac{\sum_1^{n-1} C_i / C_n}{n-1}$$

where n is the total number of years (i.e., 13), and C_i the cumulative number of citations in the i-th year. Since the cumulative citation ratio is monotonically increasing, a paper accumulates its citations faster would rise early and then stay at the high level, so it would have a high value of *citation speed*. This measure takes value between 0 and 1. Because this ratio-based measure might not be very reliable when the denominator is too small, so when running regressions using this measure as the dependent variable, we excluded papers with fewer than 12 citations (which is the median value in our data). Nevertheless, results are robust if we relax this restriction.

For all our regressions, we incorporated journal fixed effects to control for (1) unobserved topic/subfield heterogeneities at a very refined level and (2) journal reputation effects (Judge, Cable, Colbert, & Rynes, 2007). Therefore, we estimated the within-journal effects, in other words, we were evaluating the association between interdisciplinarity and citations among papers published in the same journal. In addition, the following variables were incorporated as controls: the number of authors, the number of countries, the number of pages, and the number of references. Descriptive statistics and Spearman correlations are reported in Table 2. The numbers of authors, pages, and references are skewed so that their natural logarithms were used in regression analyses. The number of countries is still highly skewed after logarithm transformation, so we created a dummy variable, *international*: 1 if the paper has authors from more than one country, and 0 otherwise. In our sample, about 19% of the papers are internationally coauthored.

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We estimated the fixed effects least squares models for *citation speed*, which is roughly normally distributed. Specifically, we implanted the *xtreg* function in *STATA*, which is equivalent to a standard OLS regression with a complete set of journal dummies. In addition, robust standard errors are clusters at journals. When analyzing the number of long- and short-term citations, the fixed-effects Poisson models with robust standard errors were estimated. Because citation counts are over-dispersed count variables, we used Poisson regression with robust standard errors, following previous literature (Hall & Ziedonis, 2001; Hottenrott & Lopes-Bento, 2014; Somaya, Williamson, & Zhang, 2007). An alternative is the negative binomial model. However, because the Poisson model is in the linear exponential class, Gourieroux, Monfort, and Trognon (1984) have shown that the Poisson estimator and the robust standard errors are consistent so long as the mean is correctly specified even under misspecification of the distribution, but the negative binomial estimator is inconsistent if the true underlying distribution is not negative binomial. Therefore, we adopted the Poisson model with robust standard errors in our empirical analysis. Furthermore, we incorporated journal fixed effects. Such fixed effects Poisson models can be fitted by conditioning out the individual fixed effects (Hausman, Hall, & Griliches, 1984). Specifically, we used the *xtpoisson* command in *STATA*, which implements the formula presented in Wooldridge (1999).

3. Results

3.1. Decomposing interdisciplinarity

We used the following variables in the factor analysis: log number of referenced subject categories, ratio of references to other subject categories, 1 – Gini, Simpson index, Shannon entropy, average dissimilarity between referenced subject categories, and Rao-Stirling diversity. As plotted in Figure 1, the first three eigenvalues are greater than 1, so 3 factors should be retained according to Kaiser's rule. Different criteria for different eigenvalues based on Horn's parallel analysis are also plotted (triangles), which form a downward slopped curve. The conclusion is also 3 factors. Raiche's nongraphic solutions for Cattell's scree test lead to conflicting conclusions: the optimal coordinate approach suggests 3 factors, while the acceleration factor approach suggests 1 factor to retain. Considering (1) the consensus between the classic Kaiser's rule and Horn's parallel analysis, (2) the divergence in this recent nongraphic solution for Cattell's scree test, and (3) that the optimal coordinate solution actually agrees with the more conventional approaches. We decided to retain 3 factors.

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Subsequently, we extracted 3 factors using the varimax rotated principal components method, and the cumulative proportion variance explained is 0.89. Factor loadings are reported in Table 3. Simpson index and Shannon entropy have the highest loading on the first factor, which reflects the variety aspect of disciplinary diversity. 1 – Gini has the highest loading on the second factor, which reflects balance, and the average dissimilarity between referenced subject categories has the highest loading on the third factor, which reflects disparity. The results are also in line with Harrison and Klein (2007) that Simpson index and Shannon entropy reflect more on variety, while Gini reflects more on unbalance[†].

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3.2. Interdisciplinarity and long-term impact

We first estimated the fixed effects Poisson models using the long-term citation counts as the dependent variable and original interdisciplinarity measures as the independent variables (Table 4). For each interdisciplinarity measure, we first fitted a model with the linear term and subsequently added the squared term to test its potential non-linear relationship with long-term citation impact. Taking Rao-Stirling diversity as an example (column 13), holding that the papers are published in the same journal, with the same number of authors, pages, and references, and have the same status in terms of whether being internationally coauthored, the number of expected long-term citations increases by 58% as Rao-Stirling diversity increases by 1, (the theoretical minimum and maximum values are 0 and 1 respectively, and the observed minimum and maximum values are 0.01 and 0.44 respectively). Furthermore, as shown in column 14, the quadratic term is insignificant, while the linear term is still significantly positive. The estimated citations by each original interdisciplinarity measure are also plotted in Figure 2A for a better visual inspection. These plots are based on models with both linear and quadratic terms (i.e., column 2, 4, 6, 8, 10, 12 and 14 respectively), holding the log number of authors, pages, and references at their means, international at 0, and journal fixed effect being 0. Four types of relationship with citations are observed: (1) The log number of referenced subject categories, Simpson index, Shannon entropy, and Rao-Stirling diversity have positive relationships with the number of citations, in line with Steele and Stier (2000). Furthermore, long-term citations increase with these variables at an increasing rate. (2) The average dissimilarity between referenced subject categories and Rao-Stirling also have positive relationships with long-term citations, but citations increases with them at a decreasing rate (although insignificant). (3) The

[†] In Harrison and Klein (2007), Simpson index is referred to as Blau index, Shannon entropy as Teachman entropy, and unbalance as disparity.

ratio of references to other subject categories has an inverted *U*-shaped relationship with citations, in line with Larivière and Gingras (2010). (4) 1 – Gini has insignificant relationship with long-term citations. However, this could be because of its high correlation with the number of references. If we exclude the number of references as a control variable, we would observe a strong negative effect of 1 – Gini. The divergent results suggest that the low consensus in previous literature regarding the relationship between interdisciplinarity and citation impact may be partially explained by their different choice of the interdisciplinarity measures.

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Table 5 reports fixed effects Poisson models using the extracted interdisciplinarity factors as independent variables. Variety, balance, and disparity are the three extracted factors, and they follow the standard normal distribution with mean equals to 0 and standard deviation equals to 1. Holding that the papers are published in the same journal, with the same number of authors, pages and references, and have the same status in terms of whether being internationally coauthored, the number of expected long-term citations increases by 1.48% as variety increases by 1 standard deviation (column 1), decreases by 2.45% as balance increases by 1 standard deviation (column 3), and increases by 5.77% as disparity increases by 1 standard deviation. Squared terms are subsequently added to test the non-linearity in these relationships. On the one hand, the square terms of variety and disparity are significant, suggesting nonlinear relationships. On the other hand, the squared term of balance is insignificant, suggesting a simply linear relationship. Figure 2B plots the estimated long-term citations with variety, balance, and disparity, based on column 2, 4, and 6 in Table 5, respectively. Again, for these estimations, we fix journal fixed effect at 0, international at 0, and all other variables at their mean.

We observe that long-term citations increase at an increasing rate with variety, which is in line with the information processing perspective that cognitive variety is very important for creative and innovative work (Lee, Walsh, & Wang, 2014; Page, 2007; Simonton, 2003). For interdisciplinary research, integrating knowledge from more disciplines contributes to potentially more broadly useful outcomes.

We also observe a negative relationship between balance and citation impact, which is also in line with Uzzi, Mukherjee, Stringer, and Jones (2013) that a paper with both higher novelty and conventionality are more likely to be a top cited paper. In other words, a paper is more likely to be top cited if it is embedded at the core of a discipline (drawing most of its prior knowledge/references from one discipline) while at the same time borrows some knowledge from some remote disciplines. However, the reason for this negative association between long-term citations and balance is still unclear. On the one hand, it could be that interdisciplinary research driving evenly by different disciplinary logics is more likely to fail in integrating these logics into something useful. Therefore, having one disciplinary core and simultaneously borrowing knowledge from other disciplines is a more effective research strategy, compared with drawing knowledge evenly from multiple disciplines. On the other hand, it could be that the current science system is biases against balanced interdisciplinary research. There are anecdotes that balanced interdisciplinary research which truly transcend disciplinary boundaries is difficult to evaluate and more likely to be unnoticed, simply because most scientists are trained within a discipline and unable to realize its value, although such balanced interdisciplinary research is very novel and broadly useful.

In addition, we observe that long-term citations increase with disparity but at a decreasing rate. This is in line with the combinatorial novelty literature that combining more remote disciplines is more novel than combining neighboring disciplines (Lee et al., 2014; Uzzi et al., 2013). Furthermore, there is a rather complex dynamics between novelty and impact. On the one hand, novelty is important for generating impact. On the other hand, a highly novel paper might not be useful or helpful for other scientists to further build on it, and therefore would fail to generate high impact (Latour & Woolgar, 1986; Merton, 1973; Whitley, 2000). We do observe that that the marginal return from disparity is decreasing. It's possible that the effect of disparity on long-term citations might turn into a negative one after certain point, but this threshold is about six standard deviations above the mean, which is beyond the maximum disparity value in our data.

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3.3. Interdisciplinarity and citation delay

The preceding section demonstrates distinct relationships between long-term citation impact and variety, balance and disparity, and this section investigates how interdisciplinarity affects the process of citation accumulation. First, we estimated fixed effects Poisson models using the short-term citations as the dependent variable (Table 6). Variety and disparity have significantly negative effects on short-term citation, while balance has no significant effects. Therefore, although variety and disparity contribute to a higher impact in the long run, their positive effects takes time to show and are not observable in the short run. On the contrary, they lead to lower citation impact in the short run. In addition, although balance lead to lower impact in the long run, its disadvantage also takes time to show and is unobservable in the short run.

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Table 7 reports fixed effects least squares models with *citation speed* as the dependent variable. Both variety and disparity have significantly negative relationships with citation speed, indicating that interdisciplinary papers with higher level of variety or disparity are more likely to encounter citation delay: being relatively cited less in the short run but cited more in the long run. In addition, balance has a positive relationship with citation speed. Meaning that interdisciplinary papers with higher level of balance is less likely to encounter citation delay. This is because these papers have an early rise and early decline in their process of citation accumulation: they receive their limited number of citation in the short run and then quickly cease to be cited.

Results for the control variables might also be worth noting. Comparing papers published in the same journal with the same number of authors, pages, and references, Internationally coauthored papers do not have significantly more citations than single country papers, in both the short run and the long run. However, they do have a higher citation speed, indicating that being internationally coauthored does contribute to faster knowledge diffusion. In addition, the number of authors and references have significantly positive effects on both short-term and long-term citations, and they also have positive effects on citation speed. It suggests that the number of authors and pages contribute to not only higher citation impact but also faster citation accumulation process. In other words, the benefits of more authors or more references is stronger in the short run and slowly decline in the long run (but still not completely fade away.) Furthermore, the number of pages has a slightly different influence on citations. The number of pages have positive effects on both short-term and long-term citations, but a negative effect on citation speed. Therefore, the number of pages does not help to attract citations faster but has a more enduring effect. Its positive effect on citations strengthens overtime.

3.4. Robustness tests

We have done a number of analyses to test the robustness of our findings. First, we used the conditional fixed effects Poisson models to analyze citation counts and incorporated robust standard errors to deal with over-dispersion in the data. Given that the negative binomial models are also commonly used in the literature, we also tried the negative binomial models. We incorporated journal fixed effects in our regressions to estimate within-journal effects, and such models can be estimated by a conditional maximum likelihood method which conditions out journal fixed effects (Cameron & Trivedi, 2013; Hausman et al., 1984; Wooldridge, 1999). Specifically, we implanted the *xtpoisson* function in STATA (StataCorp, 2013b). Hausman et al. (1984) also developed a conditional maximum likelihood strategy for negative binomial models, which is implemented in the *xtnbreg* function in STATA (StataCorp, 2013a). However, this method allows for individual-specific variation in the dispersion parameter rather than in the conditional mean, and therefore does not qualify as a true fixed effects method (Allison & Waterman, 2002; Greene, 2005; Guimarães, 2008). We fitted the *xtnbreg* models for a robustness check, note that some between-journal differences may still remain in the estimates. We got consistent results, except that the effects of balance on short-term citations became significantly negative (which is insignificantly negative in Table 6). However, this inconsistency does not challenge our conclusions.

In addition, we used alterative measures to capture the speed of citation accumulation or citation delay: (1) the ratio between accumulative citation counts in year 3 and in year 13, and (2) the year when the paper gets 50% of its total citation counts (Costas, Bordons, van Leeuwen, & van Raan, 2009). Results are robust. Furthermore, we excluded papers with fewer than 12 (which is the median) citations from the regressions. We also ran regressions without such constraints and got consistent results.

Furthermore, journals are sometimes assigned to multiple subject categories in WoS. It is possible that a paper with only one reference would have two or more referenced subject categories because this one reference is from a journal with multiple subject categories. This may cause problems for our interdisciplinarity measures. Therefore, we used the more aggregated ECOOM discipline (68 disciplines) classification scheme (Glänzel & Schubert, 2003) instead of the WoS subject categories, since using more aggregated field classifications would reduce the instances of journals having multiple field assignments and therefore would mitigate the potential measurement issues. Results remained consistent. Another related issue pertains to multidisciplinary journals, since the disciplinary memberships of papers published in these journals are not so clear. We excluded references in the "multidisciplinary sciences" subject category in our interdisciplinarity measure, and got consistent results.

In addition, because the average dissimilarity between referenced subject categories and Rao-Stirling diversity require at least two referenced subject categories, we excluded papers with fewer referenced subject categories from the analyses. Using the whole sample and running regressions for the rest interdisciplinarity measures, we also got consistent results.

However, as a bibliometric study, this paper cannot avoid some fundamental limitations in the biliometric data, such as potential errors in the use of citations as a measure of scientific impact (Bornmann & Daniel, 2008; Martin & Irvine, 1983; Wang, 2014). In addition, our interdisciplinarity measures are based on references in the scientific outputs and therefore cannot capture the knowledge integration in the interdisciplinary research process (Wagner et al., 2011).

4. Conclusions

This paper studies three different aspects of interdisciplinarity and investigates their distinct relationships with citation impact and citation delay. The factor analysis extracts three main factors underlying various interdisciplinarity measures, and these three factors correspond to variety, balance, and disparity, respectively. Regression analysis further uncovers their different relationships with long-term citation impact: long-term citations (1) increase at an increasing rate with variety, (2) decrease with balance, and (3) increase at a decreasing rate with disparity. Furthermore, although variety and disparity have positive effects on long-term citations, they have negative effects on short-term citations. In addition, although balance has a negative effect on long-term citations, such negative effect is insignificant in the short run.

This paper contributes to future interdisciplinarity research and science policy. First, we advocate the idea of using different interdisciplinarity measures in different contexts. This paper demonstrates that various interdisciplinarity measures bear non-identical relationships with citation impact. Interdisciplinarity is an abstract and multidimensional concept, and different aspects of interdisciplinarity may (1) respond to certain individual, team, or institutional factors in completely different ways, and (2) have unique consequences in terms of usefulness or impact. Furthermore, various theories which might shed light on interdisciplinarity research have their own unique focuses. For example, the information processing perspective focuses on cognitive variety, while the combinatorial novelty literature emphasizes disparity. Therefore, it's important to choose a suitable interdisciplinarity measure consistent with the invoked theory and focal research question.

Second, this paper suggests a more refined policy agenda for encouraging interdisciplinary research. This paper pushes forward the research on the relationship between interdisciplinarity and scientific impact: from a dichotomous question of whether interdisciplinary research draws higher impact towards a more complicated question about differentiated dynamics underlying different aspects of interdisciplinarity. Answers to this more complicated question is also important for more effective science policies. As science increasingly deals with boundary-spanning problems, various policy and funding initiatives have been developed to encourage interdisciplinary research, such as the US National Science Foundation (NSF) solicited interdisciplinary programs, the US National Institutes of Health (NIH) common fund's interdisciplinary research program, European Research Council (ERC) synergy grants, and UK Research Councils' cross-council funding agreement. However, interdisciplinarity is an abstract and multidimensional concept, and nuanced understanding of these different dimensions and their consequences are important for effective policies. Specifically, the positive relationship between variety and citation impact demonstrates the benefits of cognitive variety for creative work. Therefore, policy and funding initiatives can encourage research across more disciplinary boundaries and integrating knowledge from more disciplines. Furthermore, the positive relationship between disparity and citation impact also suggests potential improvements from encouraging interdisciplinary research across more remotely connected disciplines. However, since the positive marginal effect is decreasing, the policy might not want to push too far. It's possible that disparity effect on citations might turn into a negative one when the disparity is too high, that is, integrating disciplines too far apart may fail to find a common ground to produce something useful. In addition, the negative relationship between balance and citation impact may suggest that the most effective interdisciplinary research strategy in terms of generating impact is to have one disciplinary core and simultaneously borrow knowledge from some other disciplines, instead of drawing knowledge evenly from multiple disciplines without a disciplinary core. It's possible that research driving evenly by different disciplinary logics fails to integrate these logics into something useful. On the other hand, this might also suggest that balanced interdisciplinary research is biased against in the current discipline-based science system, in which scientists are mostly trained within a single discipline and therefore fail to realize the value of balanced interdisciplinary work which truly transcends interdisciplinary bounties. However, further research is required to better understand this problem. Specifically, to claim the bias against balanced interdisciplinary research, we need to estimate the unbiased should-be scientific impact first and then compare it with the observed citations. To recommend policies encouraging unbalanced instead of balanced interdisciplinary research, we would also need to test the usefulness or value of the papers directly, instead of only examining citation counts.

Third, this paper suggests a longer citation time window for evaluating interdisciplinary research. Although variety and disparity have significantly positive effects on long-term citations, they have negative effects on short-term citations. Therefore, if we adopt a very short citation time window, we would systematically underestimate the impact of interdisciplinary papers with higher level of variety and disparity. In addition, this paper also demonstrates that the dynamic process of citation accumulation is an important aspects to be investigated in interdisciplinarity studies and other science studies, in addition to the long-term citation impact.

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Table 1. Interdisciplinarity measures

Measure	Description
Ratio of references to other subject categories	
Number of referenced subject categories	n
1 – Gini	$$1-\frac{\sum(2i-n-1)x_i}{n\sum x_i}$$ where i is the index, x_i is the number of references to the i-th subject category, and subject categories are sorted by x_i in non-decreasing order.
Simpson index	$$1-\sum {p_i}^2$$ where $p_i = x_i/X$, and $X = \sum x_i$
Shannon entropy	$$-\sum p_i log(p_i)$$
Average dissimilarity between referenced subject categories	$$\frac{1}{n(n-1)}\sum_{i\neq j} d_{ij}$$ where d_{ij} is the dissimilarity between subject category i and j. Specifically, $d_{ij} = 1 - s_{ij}$, where s_{ij} is the cosine similarity between subject category i and j based on their co-citation matrix.
Rao-Stirling diversity	$$\sum_{i\neq j} p_i p_j d_{ij}$$

Table 2. Descriptive statistics and Spearman correlations (*N* = 646669)

	vars	mean	sd	min	max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Citations (14-year)	25.82	58.45	0	10058													
2	Citations (3-year)	4.47	9.31	0	1147	.80												
3	Citation speed	0.55	0.14	0.08	1	-.18	.29											
4	Authors	4.19	7.15	1	744	.21	.23	.08										
5	Countries	1.24	0.61	1	22	.09	.10	.03	.21									
6	Pages	8.93	6.91	1	452	.14	.07	-.11	-.18	.06								
7	Refs	15.03	12.59	1	615	.48	.50	.11	.23	.08	.21							
8	Referenced SCs	6.33	3.63	2	43	.36	.34	.03	.22	.04	.16	.69						
9	Ratio oth-disc refs	0.49	0.31	0	1	-.02	.00	.03	.05	-.01	-.06	.09	.29					
10	1 – Gini	0.67	0.16	0.15	1	-.40	-.40	-.07	-.18	-.06	-.19	-.81	-.57	.09				
11	Simpson	0.68	0.15	0.03	0.95	.21	.19	-.01	.16	.02	.07	.36	.84	.42	-.09			
12	Shannon	1.43	0.51	0.07	3.22	.27	.25	.01	.19	.03	.10	.49	.94	.38	-.29	.97		
13	Avg dissimilarity	0.76	0.10	0.23	1	-.01	-.11	-.18	-.11	-.03	.16	-.08	.16	.06	.01	.18	.19	
14	Rao-Stirling	0.25	0.07	0.01	0.44	.09	.02	-.11	.05	-.01	.09	.11	.64	.36	.05	.83	.79	.57

N=64669

Table 3. Factor loading

	Factor 1	Factor 2	Factor 3
ln(referenced SCs)	0.78	-0.59	0.15
Ratio oth-disc refs	0.67	0.35	-0.17
1 – Gini	-0.07	0.94	0.05
Simpson	0.93	-0.11	0.18
Shannon	0.91	-0.32	0.18
Avg dissimilarity	0.09	0.00	0.95
Rao-Stirling	0.77	0.04	0.59

Cumulative proportion variance explained: 0.89.

Table 4. Fixed effects Poisson models with original interdisciplinarity measures (N = 646223)

	Long-term citations (14-year)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ln(authors)	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
International	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(pages)	0.40***	0.40***	0.40***	0.40***	0.40***	0.40***	0.41***	0.41***	0.41***	0.41***	0.40***	0.40***	0.40***	0.40***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ln(refs)	0.27***	0.27***	0.31***	0.30***	0.31***	0.31***	0.30***	0.30***	0.29***	0.29***	0.30***	0.30***	0.30***	0.30***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(referenced SCs)	0.08***	-0.01												
	(0.01)	(0.04)												
$(\ln(\text{referenced SCs}))^2$		0.02*												
		(0.01)												
Ratio oth-disc refs			-0.08***	0.32***										
			(0.02)	(0.05)										
$(\text{Ratio oth-disc refs})^2$				-0.40***										
				(0.04)										
1-Gini					0.01	0.03								
					(0.03)	(0.17)								
$(1\text{-Gini})^2$						-0.01								
						(0.12)								
Simpson							0.18***	-0.30*						
							(0.04)	(0.12)						
Simpson^2								0.40***						
								(0.11)						
Shannon									0.07***	0.00				
									(0.01)	(0.03)				
Shannon^2										0.02^{+}				
										(0.01)				
Avg dissimilarity											0.43***	1.02**		
											(0.07)	(0.35)		
$(\text{Avg dissimilarity})^2$												-0.41		
												(0.25)		
Rao-Stirling													0.58***	0.65*
													(0.08)	(0.29)
$(\text{Rao-Stirling})^2$														-0.16
														(0.57)
Journal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Log pseudolikelihood	-8637695	-8637136	-8641587	-8635054	-8644074	-8644073	-8640234	-8639142	-8638382	-8638061	-8635233	-8635032	-8635015	-8635008
χ^2	3098***	3228	3001***	3698***	2941***	3174***	3005***	3092***	3050***	3053***	4083***	4066***	3903***	4175***

Cluster-robust standard errors in parentheses.
*** p<.001, ** p<.01, * p<.05, $^{+}$ p<.10.

Table 5. Fixed effects Poisson models: interdisciplinarity and long-term impact (*N* = 646223)

	Long-term citations (14-year)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(authors)	0.1588***	0.1586***	0.1600***	0.1600***	0.1590***	0.1586***	0.1578***	0.1575***
	(0.0105)	(0.0105)	(0.0106)	(0.0106)	(0.0110)	(0.0110)	(0.0107)	(0.0107)
International	-0.0009	-0.0008	-0.0013	-0.0013	-0.0025	-0.0025	-0.0023	-0.0022
	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0135)	(0.0135)	(0.0133)	(0.0133)
ln(pages)	0.4054***	0.4055***	0.4022***	0.4019***	0.3958***	0.3963***	0.3965***	0.3965***
	(0.0295)	(0.0295)	(0.0295)	(0.0294)	(0.0301)	(0.0302)	(0.0300)	(0.0300)
ln(refs)	0.3021***	0.3013***	0.2868***	0.2871***	0.3056***	0.3045***	0.2855***	0.2836***
	(0.0078)	(0.0077)	(0.0105)	(0.0105)	(0.0082)	(0.0083)	(0.0118)	(0.0119)
Variety	0.0148*	0.0162*					0.0137^{+}	0.0154^{+}
	(0.0061)	(0.0064)					(0.0078)	(0.0083)
Variety^2		0.0052*						0.0044^{+}
		(0.0026)						(0.0026)
Balance			-0.0245**	-0.0241**			-0.0194^{+}	-0.0194^{+}
			(0.0074)	(0.0073)			(0.0106)	(0.0108)
Balance^2				0.0009				0.0021
				(0.0033)				(0.0030)
Disparity					0.0577***	0.0535***	0.0528***	0.0488***
					(0.0075)	(0.0074)	(0.0088)	(0.0087)
Disparity^2						-0.0045^{+}		-0.0036
						(0.0025)		(0.0025)
Journal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Log pseudolikelihood	-8642990	-8642683	-8642595	-8642588	-8629711	-8629503	-8628738	-8628365
χ^2	2946***	2957***	2967***	2961***	4450***	4438***	4552***	4807***

Cluster-robust standard errors in parentheses.
*** p<.001, ** p<.01, * p<.05, $^{+}$ p<.10.

Table 6. Fixed effects Poisson models: interdisciplinarity and short-term impact (N = 644956)

	Short-term citations (3-year)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(authors)	0.2013***	0.2015***	0.2002***	0.2001***	0.2011***	0.2007***	0.2018***	0.2016***
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0140)	(0.0140)
International	0.0095	0.0094	0.0097	0.0097	0.0102	0.0102	0.0100	0.0099
	(0.0142)	(0.0142)	(0.0141)	(0.0141)	(0.0138)	(0.0139)	(0.0138)	(0.0138)
ln(pages)	0.2501***	0.2500***	0.2512***	0.2512***	0.2548***	0.2554***	0.2536***	0.2545***
	(0.0284)	(0.0284)	(0.0284)	(0.0283)	(0.0288)	(0.0288)	(0.0286)	(0.0286)
ln(refs)	0.3795***	0.3802***	0.3736***	0.3735***	0.3760***	0.3747***	0.3757***	0.3768***
	(0.0079)	(0.0079)	(0.0093)	(0.0091)	(0.0082)	(0.0083)	(0.0104)	(0.0106)
Variety	-0.0130*	-0.0143*					-0.0088	-0.0116
	(0.0054)	(0.0057)					(0.0075)	(0.0080)
Variety^2		-0.0050*						-0.0043$^+$
		(0.0020)						(0.0023)
Balance			-0.0024	-0.0026			-0.0037	-0.0022
			(0.0072)	(0.0075)			(0.0115)	(0.0121)
Balance^2				-0.0003				-0.0016
				(0.0034)				(0.0030)
Disparity					-0.0237*	-0.0297**	-0.0229*	-0.0283*
					(0.0094)	(0.0095)	(0.0116)	(0.0113)
Disparity^2						-0.0051*		-0.0056*
						(0.0021)		(0.0023)
Journal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Log pseudolikelihood	-1992283	-1992235	-1992423	-1992423	-1991992	-1991944	-1991906	-1991818
χ^2	3981***	3996***	3933***	4149***	5223***	5198***	5414***	5519***

Cluster-robust standard errors in parentheses.
*** p<.001, ** p<.01, * p<.05, $^+$ p<.10.

Table 7. Fixed effects least squares models: interdisciplinarity and citation speed (N = 332649)

	Citation speed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(authors)	0.0054***	0.0055***	0.0052***	0.0052***	0.0053***	0.0053***	0.0055***	0.0055***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
International	0.0011*	0.0011*	0.0012**	0.0012**	0.0013**	0.0013**	0.0013**	0.0013**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln(pages)	-0.0158***	-0.0158***	-0.0154***	-0.0153***	-0.0140***	-0.0140***	-0.0143***	-0.0141***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
ln(refs)	0.0188***	0.0190***	0.0194***	0.0194***	0.0183***	0.0182***	0.0199***	0.0202***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0004)	(0.0006)	(0.0006)
Variety	-0.0030***	-0.0034***					-0.0021***	-0.0027***
	(0.0003)	(0.0004)					(0.0004)	(0.0004)
Variety^2		-0.0010***						-0.0009***
		(0.0002)						(0.0002)
Balance			0.0019***	0.0019***			0.0011**	0.0014**
			(0.0004)	(0.0004)			(0.0004)	(0.0004)
Balance^2				-0.0001				-0.0004*
				(0.0002)				(0.0002)
Disparity					-0.0099***	-0.0101***	-0.0094***	-0.0095***
					(0.0004)	(0.0004)	(0.0004)	(0.0004)
Disparity^2						-0.0002		-0.0004$^+$
						(0.0002)		(0.0002)
Journal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
R^2 within	0.0163	0.0166	0.0157	0.0157	0.0227	0.0227	0.0230	0.0232
F	563***	472***	549***	461***	696***	584***	501***	355***

Cluster-robust standard errors in parentheses.
*** p<.001, ** p<.01, * p<.05, $^+$ p<.10.

Figure 1. Determining the number of factors

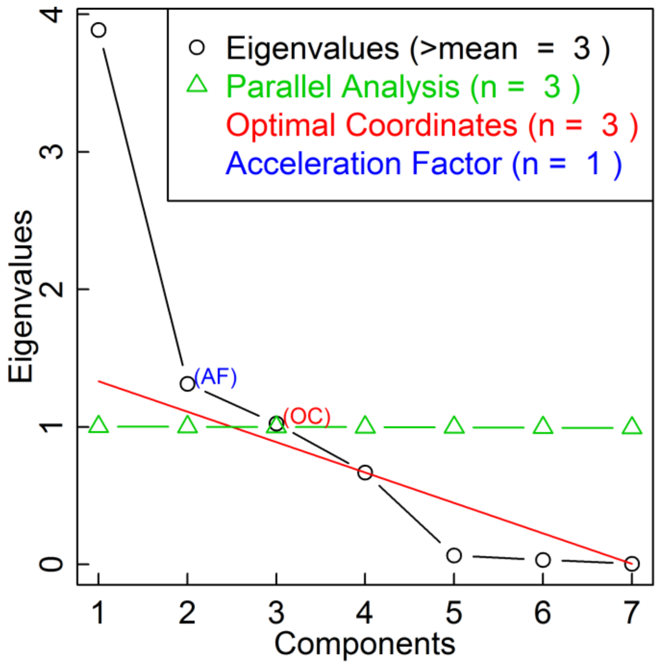
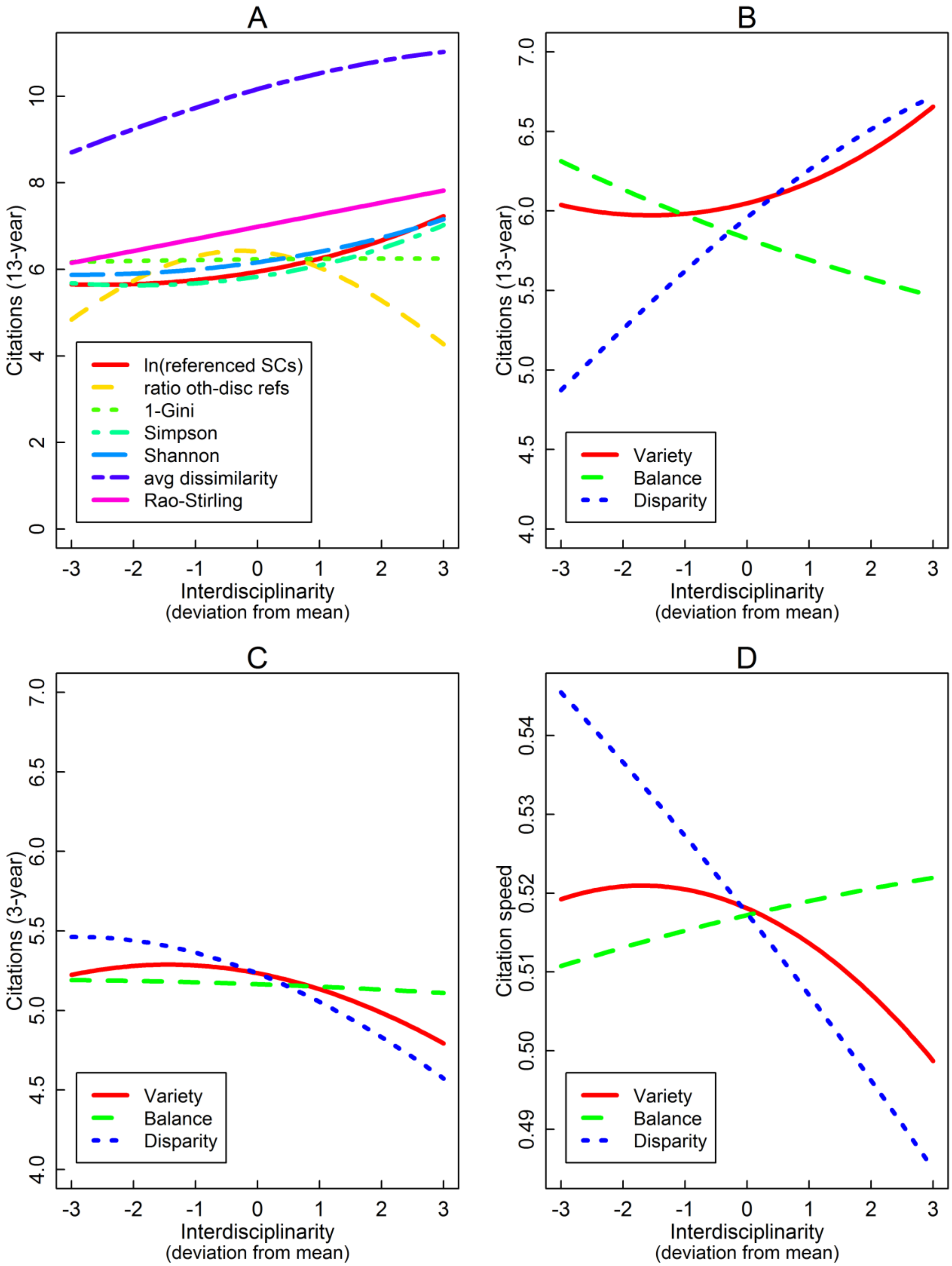


Figure 2. Interdisciplinarity and citations



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